

Extracting Blink Rate Variability from EEG Signals

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Abstract—Generally, blinks are treated on equal with artifacts and noise while analyzing EEG signals. However, blinks carry important information about mental processes and thus it is important to detect blinks accurately. The aim of the presented study is to propose a blink detection method and discuss its application for extracting blink rate variability, a novel concept that might shed some light on the mental processes. In this study, 14 EEG recordings were selected for assessing the quality of the proposed blink detection algorithm.

Keywords—blink rate variability, inter blink interval dynamics, EEG artifacts.

I. INTRODUCTION

Blinking is a semiautonomic closing of the eye lids. Blinks keep eyes protected against potentially damaging stimuli, such as bright lights and foreign bodies like dust. The sudden changes in an image due to saccades or blinks does not interfere with our subjective experience of continuity [1]. The very act of blinking suppresses activity in several areas of the brain responsible for detecting environmental changes, so that one experiences the world as continuous. Researchers have shown synchronous behavior in blinking between listener and speaker in face-to-face conversation [2]. Reduced blink rate causes eye redness and dryness also known as Dry Eye, which is a major symptom of the Computer Vision Syndrome [3]. Blinks have been known to be linked to interior brain activities. Increasing the accuracy of blink detection is of high importance as humans look for easier methods of collecting internal brain activity information. The detection of the eye blinks had a huge impact in various fields. In some Brain Computer Interface (BCI) researchers analyzed eye blinks to determine the pattern and the duration between blinks. After collecting this analysis, the information was used with a device that could control a computer similarly to how we use a computer mouse. This implementation of the use of blinks has opened a wide door to new possibilities for disabled people [4]. Another area where blinks play an important role is in the prevention of car accidents. The World Health Organization (WHO) has announced that the ninth cause of death, globally, is car accidents. The National Motor Vehicle Crash Causation Survey (NMVCCS) has found that 30 percent of car accidents happen due to the drowsiness of drivers [5]. It is noted that workload increases blink rate and blink rate is known to decrease in monotonous and drowsy conditions [6]. Blink rate (BR) is inversely correlated with the increase of workload so blinks can be used to detect drowsiness before it causes

damage [6]. Researchers have shown that blinks can play a significant role in detecting many different brain disorders and brain activities. Spontaneous BR has been studied in many neurological diseases like Parkinson's disease and Tourette syndrome [7], [8], [9]. The use of blink detection does not stop there. Blinks are regarded as a non-invasive peripheral markers of central dopamine activity which makes their accurate detection more important [10], [11], [12], [13], [14], [15]. Researchers have studied the synchronicity of the eye blinks in audiences, who experienced the same method of storytelling. The eye blink synchronization among audiences is driven by attention cycles, which are in turn driven by emotional processing [16], [17], [18]. Blinks are not always the most desired signals when it comes to non-invasive brain signal measuring as many electroencephalographs (EEG) remove them to acquire brain data. Eye blink is one of the main artifacts in the EEG signals [19]. Researchers are focusing on removing these parts of the signals to obtain clean brain signal values. To analyze blinks and variation of inter-blink intervals it is important to detect blinks accurately. We propose to apply the blink detection algorithm for extracting the inter-blink intervals that we coin the blink rate variability (BRV) in analogy to heart rate variability. We construct BRV for subjects taking memory tests. We further compare the numbers of detected blinks by the algorithm and by manual counting.

II. EXPERIMENTAL SETUP

A. Data Acquisition

The video stream was captured with a Pointgrey Flea3 USB camera. Video stream was stored on a disk drive to be processed in the future. Simultaneously, EEG signals were recorded. For the recording of EEG signals, we employed a Mitsar-EEG 201 amplifier and used WinEEG software. The electrodes were placed according to the international 10-20 system [20]. Electro-gel was injected into electrodes' hollow in order to decrease the electrode-skin resistance. Currently, the EEG signals were recorded for the purpose of eye blink detection. In the future, we are planning to analyze EEG to detect various types of brain activity. The experimental setup is shown in fig.1.

B. Testing Procedures

The testing software was developed using Java in such a way that it does not require any interventions. The procedure consisted of a five minute reading session and a five minute



Figure 1. Experimental setup

memory test session. Before the memory test, a passage about Ethiopia is given. After reading the passage, users are presented questions one by one. In this paper, we focus on detecting blinks while subjects are reading the passage and answering questions about the passage. Overall, 28 people participated in the experiment. Among them 14 subjects were dropped due to falling asleep, adjusting the cap or constant head movements that resulted in significant noise.

III. EYE BLINK DETECTION PROCEDURE

Electrodes are applied to the head according to the 10-20 system. We used bipolar montage, which means we determined the potential between Fp1 and Fp3, along with Fp2 and Fp4. Fig. 2 presents EEG signals for both pairs. EEG signals were recorded while participants were taking the tests and imported in form of CSV files to Matlab for further analysis. The process of blink detection can be divided into two stages: preprocessing and blink detection. The preprocessing stage consists of the following steps: (a) normalization and bandpass filtering (b) cutting of extreme amplitudes using the estimated cumulative distribution function that characterizes the signal amplitude's distribution, (c) independent component analysis, and (d) selection of the component with eye blinks. The blink detection stage consists of (e) signal thresholding, (f) candidate extraction, and (g) polynomial fitting with finding maximum in the polynomial function. Both stages, preprocessing and blink detection, have been presented in listings algorithm 1 and algorithm 2 respectively.

The first step in the process of blink detection consists of cutting off very extreme amplitudes, that usually caused by touching the electrodes or cap adjustment. Right after, the signal is band-pass filtered and normalized. We applied 50th-order bandpass filter with finite impulse response. The lowest and highest normalized cut off frequencies are $f_L = 0.02$ and $f_H = 0.08$ correspondingly. In fig. 3 the EEG signals after bandpass filtering and normalization are presented. The signals became smoother and the lower frequency components responsible for trends in the signals disappear after filtering. For the filtered signal an amplitude cumulative distribution function (CDF) is estimated. Using the CDF, we cut 2 percent of all amplitudes from the top and 1 percent from the bottom.

input: \mathbf{X} is $2 \times N$ fp1-fp3 and fp2-fp4 signals

output: y is the blink component

H is the Heaviside function

$filt(\mathbf{X}, f_l, f_h)$ is a sub-band filter, where f_l and f_h are low and high cut off frequencies

$CDF(x)$ estimates the cumulative distribution function for x

for $k = 1$ **to** 2 **do**

$t = 6 \cdot \sigma(\mathbf{X}_k)$

if $skewness(\mathbf{X}_k) \geq t$ **then**

$\mathbf{X}_{k, \{i | \mathbf{X}_k \leq t\}} = t$

end

$\mathbf{X}_k = filt(\mathbf{X}_k, f_l, f_h)$

$\mathbf{X}_k = \frac{\mathbf{X}_k - E[\mathbf{X}_k]}{\sigma(\mathbf{X}_k)}$

$\hat{F}_{\mathbf{X}_k} = CDF(\mathbf{X}_k)$

$r = max(\mathbf{X}_k) - min(\mathbf{X}_k)$

$\mathbf{X}_{k, \{i | \mathbf{X}_k \geq x_{max}\}} = min(\mathbf{X}_k) + r \cdot F_{\mathbf{X}_k}^{-1}(0.99)$

$\mathbf{X}_{k, \{i | \mathbf{X}_k \leq x_{min}\}} = min(\mathbf{X}_k) + r \cdot F_{\mathbf{X}_k}^{-1}(0.02)$

end

$\mathbf{S} = ICA(\mathbf{X})$

if $\sum H(\|\mathbf{S}_1\| - 3 \cdot \sigma(\mathbf{S}_1)) > \sum H(\|\mathbf{S}_2\| - 3 \cdot \sigma(\mathbf{S}_2))$ **then**

$y = \mathbf{S}_1$

else

$y = \mathbf{S}_2$

end

Algorithm 1: The preprocessing stage

The next step consists of mixing signals from two pairs of electrodes fp1-fp3 and fp2-fp4 in such a way that led to a cleaner signal.

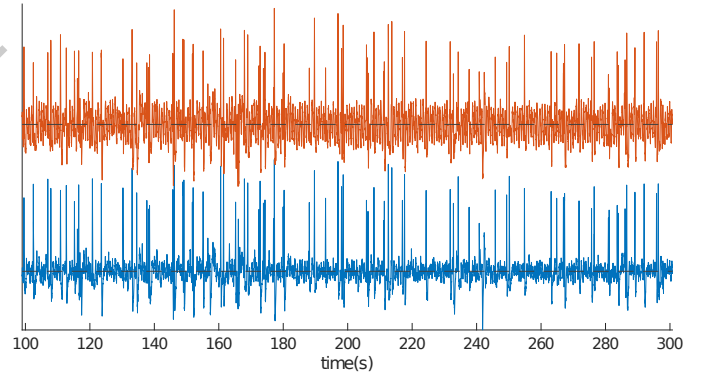


Figure 2. Original Fp1-Fp3 and Fp2-Fp4 electrode pairs

Usually, we want to get rid of ocular artifacts from EEG signals, as the eye blink is an artifact and leads to interpretation problems [21]. However, our goal is on contrary aims at extracting blinks from EEG. We employ the fastICA [22] algorithm for solving Blind Source Separation (BSS) [23], which allows us to differentiate neural activity from muscle and blinks [24]. Independent component analysis (ICA) consists of two steps. The first is responsible for decorrelation

input: y - blink component,
 f_s - sampling frequency **output:** t - position of blinks measured in samples

l_{min} - minimum arc length of a blink wave
 w_{min}, w_{max} - min/max blink duration

$\{\mathbf{Y}, \mathbf{s}\} = \text{segment}(y)$ - extracts continuous segments of non-zero values from y and stores them as a list in \mathbf{Y} , \mathbf{s} contains positions of segments in y .

$l_{min} = \frac{f_s}{50}, w_{min} = \frac{f_s}{25}, w_{max} = f_s$

$\mathbf{y}_{\{i|y < \sigma(y)\}} = 0$

$\{\mathbf{Y}, \mathbf{s}\} = \text{segment}(y)$

$l = 0$

for $j = 1$ **to** $\dim(\mathbf{Y}) - 1$ **do**

$N = \dim(\mathbf{Y}_j)$

$\mathbf{x} = \{i | 1 \leq i \leq N\}$

$\mathbf{a} \leftarrow \underset{\mathbf{a}}{\operatorname{argmin}} \|\mathbf{Y}_j - \sum_{n=0}^3 a_n \cdot (x_0^n, x_2^n, \dots, x_{N-1}^n)\|_2$

$\hat{\mathbf{y}} = (\hat{y}_0, \hat{y}_1, \dots, \hat{y}_{N-1}) = \sum_{n=0}^3 a_n \cdot (x_0^n, x_1^n, \dots, x_{N-1}^n)$

$alen = \sum_{i=0}^{N-1} \sqrt{(\hat{y}_i - \hat{y}_{i+1})^2 + 1/N}$

if $w_{min} < N$ **AND** $N < w_{max}$ **AND** $l_{min} < alen$ **then**

$v = \max \mathbf{Y}_j$

$p = \operatorname{argmax} \mathbf{Y}_j$

$\alpha_1 = \frac{180}{\pi} \cdot \operatorname{atan2}(v - \hat{y}_0, \frac{p}{f_s})$

$\alpha_2 = \frac{180}{\pi} \cdot \operatorname{atan2}(v - \hat{y}_{\dim(\mathbf{y})-1}, \frac{p}{f_s})$

if $\alpha_1 > 80$ **AND** $\alpha_2 < 100$ **then**

$t_l = \mathbf{s}_j + p - 1$

$l = l + 1$

end

end

end

Algorithm 2: The blink detection stage

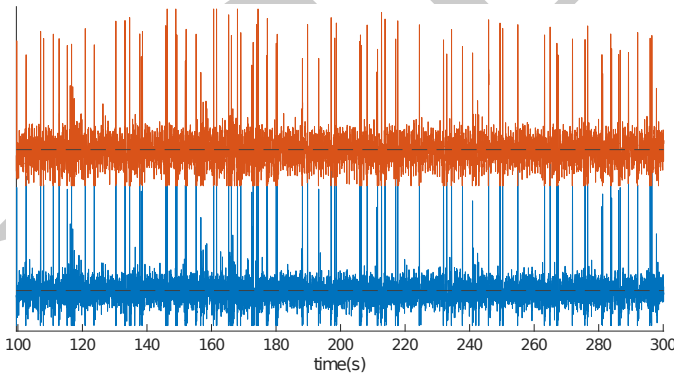


Figure 3. Normalized and band-pass filtered signals

or whitening, when a correlation in the data is removed. The second stage is responsible for the separation, which is an orthogonal transformation of whitened signals (rotation of the joint density). The task is to find an orthogonal matrix U such that the projections on the orthogonal axis are non-Gaussian [22]. One by one, we look for the rows of the matrix $U = (u_1, u_2)^T$ so a measure of non-Gaussianity $|E(G(u_k^T x_{st}))|$ is maximized by such u_k that the length of u_k is one and orthogonal to the remain row. The function G can be any nonquadratic function, which is twice continuously differentiable with $G(0) = 0$. We tested a number of nonlinear functions and the one that results in a better component separation is the $g(z) = z^2$ skewness measure. The $g(z) = z^2$ (skew) nonlinearity finds skew sources, but in the case of symmetric sources is not efficient. In our data, the skew measure shows best results due to the fact that the waveforms corresponding to blinks are asymmetrical (fig. 4). To distinguish which of the components corresponds to the blink component y , we select the component based on the following rule

$$y = \begin{cases} \sum H(|\mathbf{S}_1| - 3 \cdot \sigma(\mathbf{S}_1)) > \sum H(|\mathbf{S}_2| - 3 \cdot \sigma(\mathbf{S}_2)) & \text{blinks} \\ \text{otherwise} & \end{cases} \quad (1)$$

where H is the Heaviside function. In (1) we count a number of crossings at $3 \cdot \sigma(\mathbf{S}_2)$. At the next step, we set to zero all samples that are smaller than the standard deviation of the signal. The samples below the threshold are zeroed. The remaining contiguous segments are treated as blink candidates (fig. 4). Finally, a 3rd order polynomial function is fitted to the samples within each segment. If the arc length of the polynomial function is less than a predefined threshold, the region is rejected (fig. 5). We also reject regions with a slop of the front and the end transitions having an angle less than 80 degrees for the front and having greater than 100 degrees for the end transition. The slop is calculated as an angle of line connecting end points of the fitting polynomial and its maximum (fig. 6).

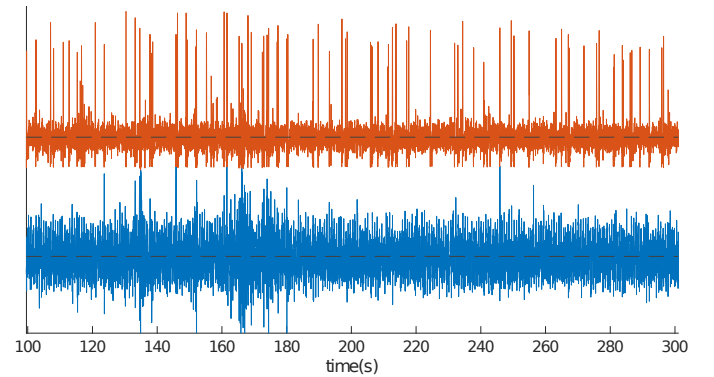


Figure 4. Independent components

To construct blink rate variability, the time of occurrences of consecutive blinks are subtracted. The interval between blinks is stack-up into a series that constitutes blink rate variability (fig. 7).

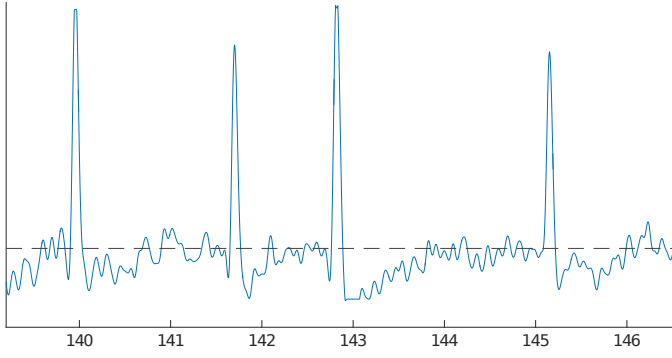


Figure 5. An independent component with blinks

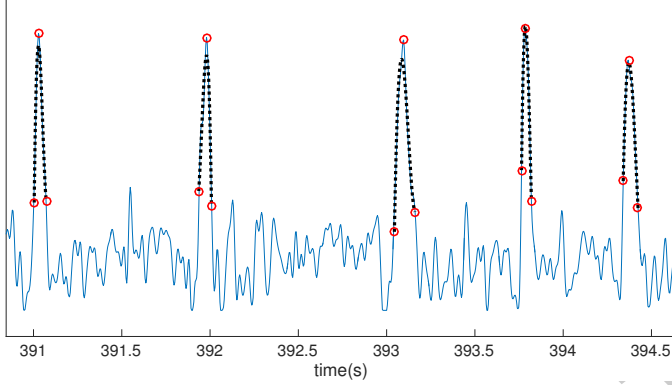


Figure 6. Detected blinks

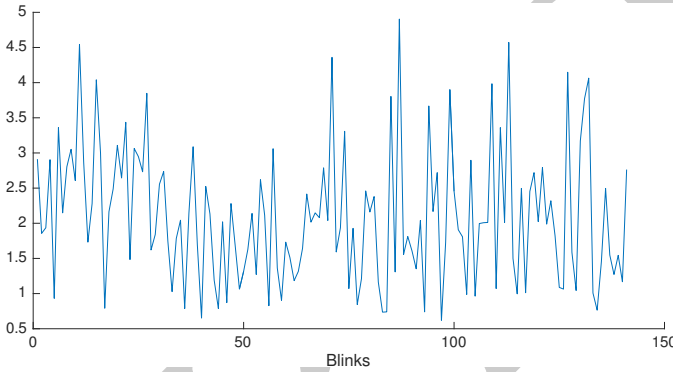


Figure 7. Example of blink rate variability

IV. RESULTS AND DISCUSSION

Figure 8 demonstrates BRVs for all of the subjects during the memory test. The abscissa is the blink interval and the ordinate represents the length of inter-blink intervals. The BRV shows the dynamics of blink intervals extracted while memory testing for each subject.

To access the quality of blink detection we manually calculated the number of false positives, false negatives and true positives during the reading and the testing stages. The false positives are mistakenly detected blinks at places where blinks did not occur. The false negatives are the blinks that were missed, and

Table I. COMPARISON OF AUTOMATIC AND MANUAL BLINK DETECTION DURING READING STAGE

Subject	False positive	False negative	True positive	Precision	Recall
1	3	0	100	0.97	1.00
2	0	3	180	1.00	0.98
3	0	0	94	1.00	1.00
4	0	0	61	1.00	1.00
5	0	0	60	1.00	1.00
6	0	1	94	1.00	0.99
7	1	0	133	0.99	1.00
8	2	1	49	0.96	0.98
9	4	1	148	0.97	0.99
10	0	0	139	1.00	1.00
11	3	0	62	0.95	1.00
12	1	0	76	0.99	1.00
13	2	3	113	0.98	0.97
14	0	1	122	1.00	0.99

the true positives are the correctly detected blinks. Based on these three categories we calculated the precision and recall characteristics that are shown in tables 1 and 2. The average precision during reading stage is 0.99 ± 0.02 and the average of recall is 0.99 ± 0.01 . The average precision during memory testing stage is 0.98 ± 0.03 and the average of recall is 0.99 ± 0.02 .

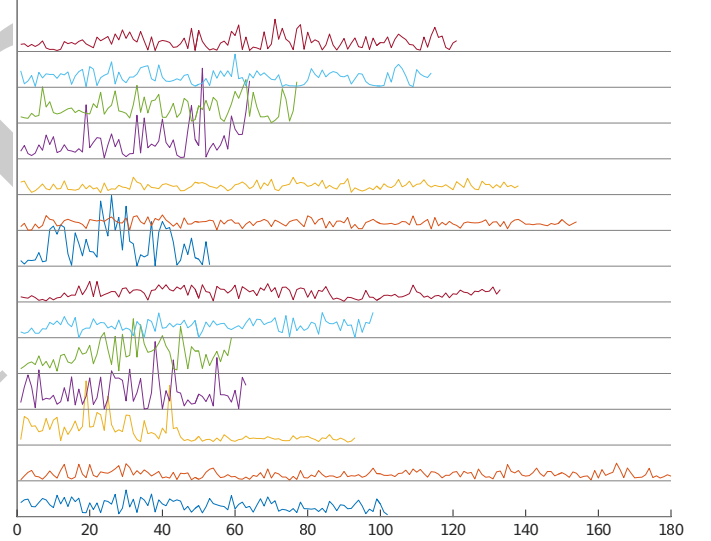


Figure 8. Extracted blink rate variability for each subject during reading

V. CONCLUSION

Blinking is a natural, biological, semiautomatic process. It is linked to interior brain activity and relationships between blinks and performing tasks. The blink rate variability might find applications in variety of fields, including car safety, psychology or BCI.

In order to automatically extract blinks from large datasets of EEG recordings, we proposed the blink detection algorithm. Basic steps such as band-pass filtering and thresholding are applied in the algorithm. Then fastICA is applied to find an independent component within the blinks. The blink candidates were filtered based on the heuristics that arc length of the blink

Table II. COMPARISON OF AUTOMATIC AND MANUAL BLINK DETECTION DURING TESTING STAGE

Subject	False positive	False negative	True positive	Precision	Recall
1	0	1	187	1.00	0.99
2	0	3	212	1.00	0.99
3	1	1	76	0.99	0.99
4	3	3	63	0.95	0.95
5	0	2	146	1.00	0.99
6	0	0	124	1.00	1.00
7	0	0	144	1.00	1.00
8	5	0	67	0.93	1.00
9	1	1	197	0.99	0.99
10	3	4	184	0.98	0.98
11	4	0	51	0.93	1.00
12	1	3	88	0.99	0.97
13	0	8	181	1.00	0.96
14	0	0	201	1.00	1.00

waveform should be above a certain threshold and the slopes of the blink waveform are within a $[80^\circ, 100^\circ]$ range. Calculated the recall and precision characteristics show that the proposed algorithm is suitable for blink rate variability extraction.

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